Project 2 Report and Code Output

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March 26, 2021

In [1]:
```
import sqlite3
import pandas
import matplotlib.pyplot as plt
import numpy as np

sqlite_file = 'lahman2014.sqlite'
conn = sqlite3.connect(sqlite_file)
```

Problem 1

In this part I made two different queries that I would later join using the pandas merge by outer. Two different queries just made it easier to visualize what was going on and it was still easy to join the two tables. For missing values, I decided that it would be enough to just drop the row that had NaN just because it meant that there was missing information for a team during a specific time period. The reason there was missing data is because it never existed in the first place. Here everything will be joined to the `teams` database which we will use for the next problems.

In [2]:
```
salary_query = "SELECT teamID, yearID, sum(salary) as total_payroll, sum(salary)/count(salary) as mean_payroll FROM Salaries GROUP BY teamID, yearID"

team_salaries = pandas.read_sql(salary_query, conn)
team_salaries.head()
```

Out[2]:

	teamID	yearID	total_payroll	mean_payroll
0	ATL	1985	14807000.0	673045.454545
1	BAL	1985	11560712.0	525486.909091
2	BOS	1985	10897560.0	435902.400000
3	CAL	1985	14427894.0	515281.928571
4	CHA	1985	9846178.0	468865.619048

Talk about missing values

In [3]:
```
team_query = "SELECT cast(W as float)/cast(G as float)*100 as win_rate, yearID, teamID, franchID, G, W FROM Teams GROUP BY teamID, yearID"
team_win_rate = pandas.read_sql(team_query, conn)
team_win_rate
```

Out[3]:

	win_rate	yearID	teamID	franchID	G	W
0	24.000000	1884	ALT	ALT	25	6
1	51.851852	1997	ANA	ANA	162	84
2	52.469136	1998	ANA	ANA	162	85
3	43.209877	1999	ANA	ANA	162	70
4	50.617284	2000	ANA	ANA	162	82
...	...	...	...	...	...	...
2770	36.507937	1887	WS8	WNL	126	46
2771	35.294118	1888	WS8	WNL	136	48
2772	32.283465	1889	WS8	WNL	127	41
2773	31.654676	1891	WS9	WAS	139	44
2774	41.228070	1884	WSU	WNA	114	47

2775 rows × 6 columns

In [4]:
```
teams = pandas.merge(team_salaries, team_win_rate, how='outer', on=['teamID','yearID'])
teams.sort_values("yearID", ascending=True)
teams = teams.dropna()
teams
```

Out[4]:

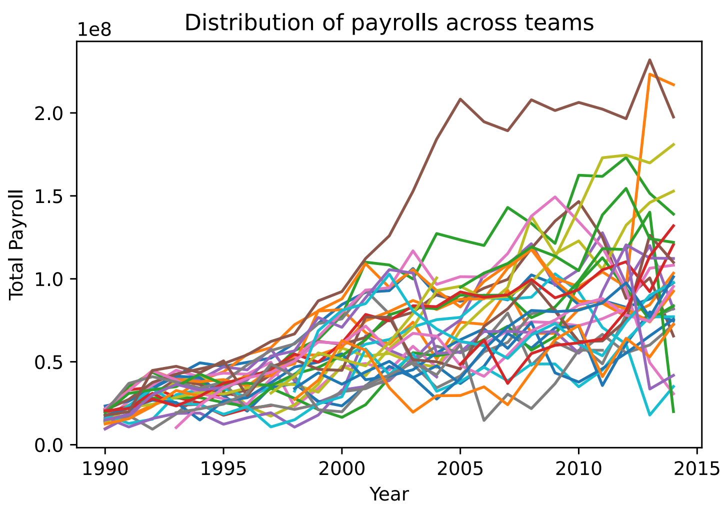
	teamID	yearID	total_payroll	mean_payroll	win_rate	franchID	G	W
0	ATL	1985	14807000.0	6.730455e+05	40.740741	ATL	162.0	66.0
1	BAL	1985	11560712.0	5.254869e+05	51.552795	BAL	161.0	83.0
2	BOS	1985	10897560.0	4.359024e+05	49.693252	BOS	163.0	81.0
3	CAL	1985	14427894.0	5.152819e+05	55.555556	ANA	162.0	90.0
4	CHA	1985	9846178.0	4.688656e+05	52.147239	CHW	163.0	85.0
...	...	...	...	...	...	...	...	...
855	SLN	2014	120693000.0	4.310464e+06	55.555556	STL	162.0	90.0
856	TBA	2014	72689100.0	2.907564e+06	47.530864	TBD	162.0	77.0
857	TEX	2014	112255059.0	4.677294e+06	41.358025	TEX	162.0	67.0
858	TOR	2014	109920100.0	4.396804e+06	51.234568	TOR	162.0	83.0
859	WAS	2014	131983680.0	4.399456e+06	59.259259	WSN	162.0	96.0

858 rows × 8 columns

Problem 2

For this problem I filtered the `teams` dataframe that I created in problem 1 to only have values from 1990 to 2014. After that, I plotted each teams payroll with respect to time. The payroll was calculated by adding up the payroll of each player in the team.

In [5]:
```
teams = teams[teams['yearID'] >= 1990]
teams = teams[teams['yearID'] <= 2014]
for team in teams['teamID'].unique():
    plt.plot(teams.loc[teams['teamID'] == team]["yearID"], teams.loc[teams['teamID'] == team]["total_payroll"])
plt.xlabel("Year")
plt.ylabel("Total Payroll")
plt.title("Distribution of payrolls across teams")
plt.show()
```



Question 1

In the previous plot, each line represents a teams payroll through time. Intuitively we can see that the amount of money these teams are getting is increasing through out all teams. We can also observe gaps forming between teams as time progresses and this means that some teams have way higher payroll than other teams.

Problem 3

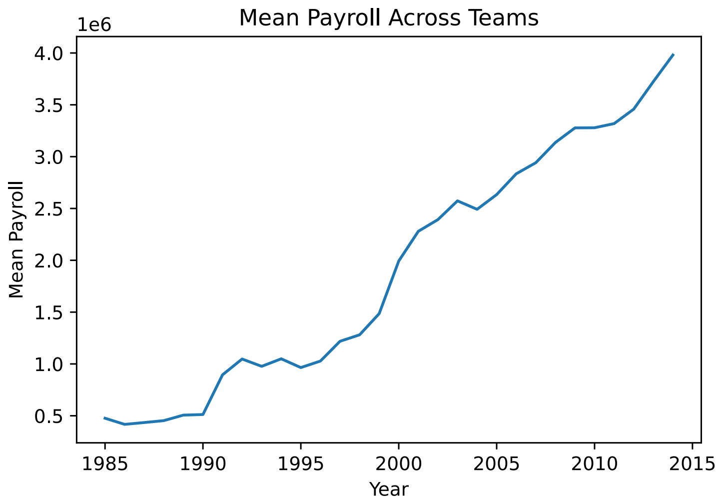
In this section I created a new SQL query to make it easier to get the mean payroll per year for the whole dataset. I could have used the `teams` dataframe but it just seemed easier to do a new SQL query. Then, I used the new data to plot the mean payroll with respect to time.

In [6]:
```
mean_query = "SELECT yearID, sum(salary)/count(salary) as mean FROM Salaries GROUP BY yearID"

mean = pandas.read_sql(mean_query, conn)
mean.head()
```

Out[6]:

	yearID	mean
0	1985	476299.447273
1	1986	417147.043360
2	1987	434729.465710
3	1988	453171.076923
4	1989	506323.081575

In [7]:
```
plt.plot(mean["yearID"], mean["mean"])
plt.xlabel("Year")
plt.ylabel("Mean Payroll")
plt.title("Mean Payroll Across Teams")
plt.show()
```



Problem 4

Here I used the `teams` dataframe I created in problem 1 to make 5 different plots. Each plot represents a small section of the data where we can see the mean win rate and mean payroll though this section in time that we are analyzing. I utilized the `pandas.groupby` function to group by teamID and get the mean for the payroll and win rate of each year. I repeated this for the 5 sections of time that we are analyzing.

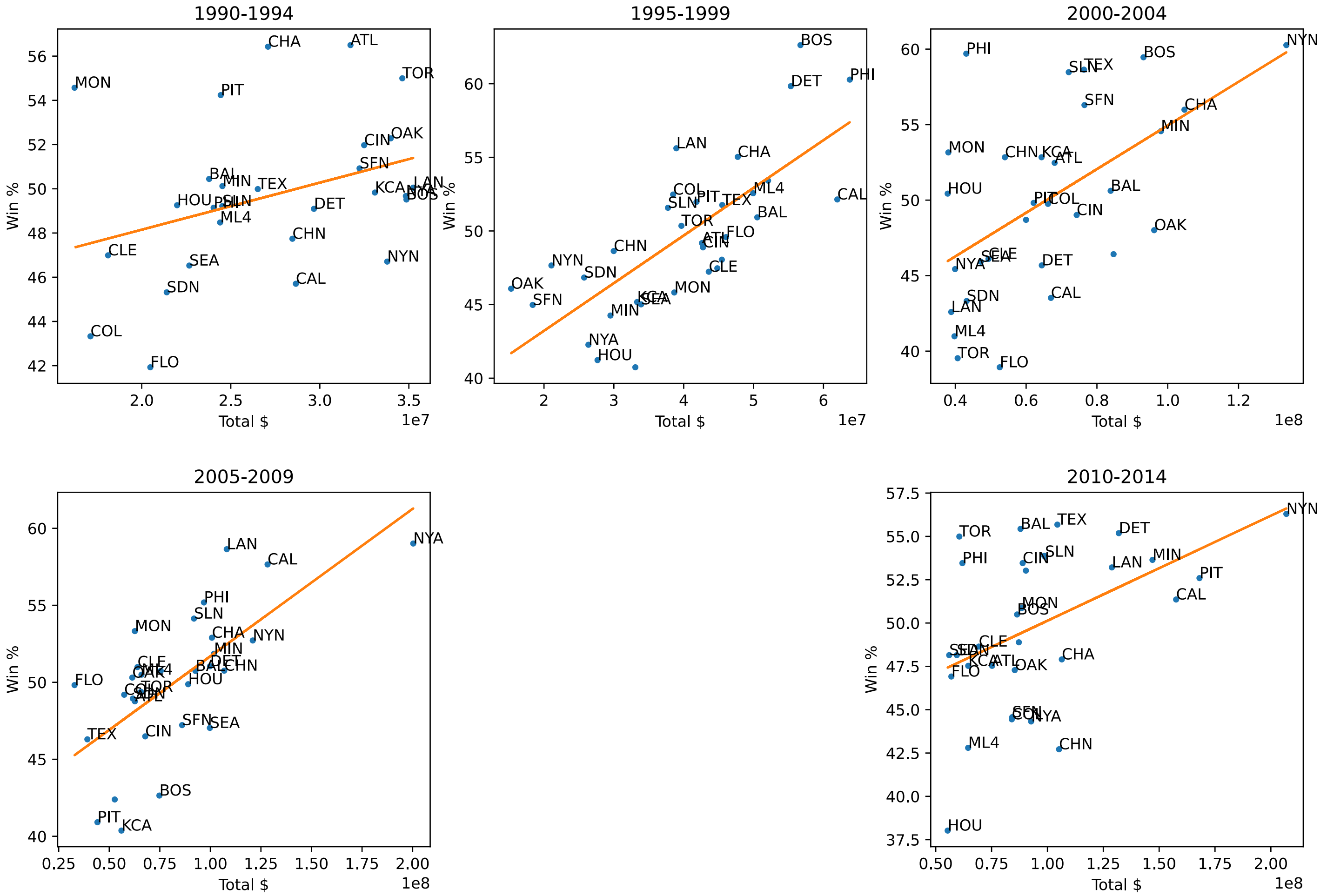
In [8]:
```
section1 = teams[(teams['yearID'] >= 1990) & (teams['yearID'] <= 1994)]
section1 = section1.groupby('teamID', as_index=False)[["total_payroll", "win_rate"]].mean()
section1.head()
```

Out[8]:

	teamID	total_payroll	win_rate
0	ATL	31721852.8	56.497726
1	BAL	23785204.0	50.444080
2	BOS	34863216.8	49.514761
3	CAL	28654777.4	45.704777
4	CHA	27090400.4	56.426308

In [9]:
```
section2 = teams[(teams['yearID'] >= 1995) & (teams['yearID'] <= 1999)]
section2 = section2.groupby('teamID', as_index=False)[["total_payroll", "win_rate"]].mean()

section3 = teams[(teams['yearID'] >= 2000) & (teams['yearID'] <= 2004)]
section3 = section3.groupby('teamID', as_index=False)[["total_payroll", "win_rate"]].mean()

section4 = teams[(teams['yearID'] >= 2005) & (teams['yearID'] <= 2009)]
section4 = section4.groupby('teamID', as_index=False)[["total_payroll", "win_rate"]].mean()

section5 = teams[(teams['yearID'] >= 2010) & (teams['yearID'] <= 2014)]
section5 = section5.groupby('teamID', as_index=False)[["total_payroll", "win_rate"]].mean()
```

In [10]:
```python
plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')

ax1 = plt.subplot(231)
ax2 = plt.subplot(232)
ax3 = plt.subplot(233)
ax4 = plt.subplot(234)
ax5 = plt.subplot(236)

plt.tight_layout(h_pad=5.0)

ax1.title.set_text('1990-1994')
ax2.title.set_text('1995-1999')
ax3.title.set_text('2000-2004')
ax4.title.set_text('2005-2009')
ax5.title.set_text('2010-2014')

ax1.set_xlabel('Total $')
ax2.set_xlabel('Total $')
ax3.set_xlabel('Total $')
ax4.set_xlabel('Total $')
ax5.set_xlabel('Total $')

ax1.set_ylabel('Win %')
ax2.set_ylabel('Win %')
ax3.set_ylabel('Win %')
ax4.set_ylabel('Win %')
ax5.set_ylabel('Win %')

ax1.plot(section1["total_payroll"], section1["win_rate"], '.')
ax2.plot(section2["total_payroll"], section2["win_rate"], '.')
ax3.plot(section3["total_payroll"], section3["win_rate"], '.')
ax4.plot(section4["total_payroll"], section4["win_rate"], '.')
ax5.plot(section5["total_payroll"], section5["win_rate"], '.')

for i, txt in enumerate(section1["teamID"]):
    ax1.annotate(txt, (section1["total_payroll"][i], section1["win_rate"][i]))
    ax2.annotate(txt, (section2["total_payroll"][i], section2["win_rate"][i]))
    ax3.annotate(txt, (section3["total_payroll"][i], section3["win_rate"][i]))
    ax4.annotate(txt, (section4["total_payroll"][i], section4["win_rate"][i]))
    ax5.annotate(txt, (section5["total_payroll"][i], section5["win_rate"][i]))


m, b = np.polyfit(section1["total_payroll"], section1["win_rate"],1)
ax1.plot(section1["total_payroll"], m * section1["total_payroll"] + b, '-')

m, b = np.polyfit(section2["total_payroll"], section2["win_rate"],1)
ax2.plot(section2["total_payroll"], m * section2["total_payroll"] + b, '-')

m, b = np.polyfit(section3["total_payroll"], section3["win_rate"],1)
ax3.plot(section3["total_payroll"], m * section3["total_payroll"] + b, '-')

m, b = np.polyfit(section4["total_payroll"], section4["win_rate"],1)
ax4.plot(section4["total_payroll"], m * section4["total_payroll"] + b, '-')

m, b = np.polyfit(section5["total_payroll"], section5["win_rate"],1)
ax5.plot(section5["total_payroll"], m * section5["total_payroll"] + b, '-')


plt.show()
```



Question 2

These graphs represent the team payrolls versus their win percentage across different time periods. We can see from our regression lines that it seems to be very consistent how the teams with the highest payrolls have the highest winrates. A team that particularly stands out at paying for wins is NYN because we can consistently see that whenever their payroll was the highest (2000-2004 and 2010-2014), their win rate was also the highest. This data makes sense because the highest skilled players would be the most expensive to have in their teams, and having good players will give the team a higher win rate. From the different graphs, we can see that Oakland A's performance varies. It seems to be consistent that the higher their payroll is, the higher their win rate. During the 1995-1999 period, they had the lowest payroll but they were also one of the worst performing teams but during 1990-1994 they had one of the highest payrolls and were on the best performing teams.

Problem 5

Here I create a new column to my `teams` dataframe where I apply the formula $standarizedpayroll = \frac{payroll - avgpayroll}{standarddeviation}$ by using the `groupby` and the `transform` functions.

In [11]:
```
teams.head()
```

Out[11]:

	teamID	yearID	total_payroll	mean_payroll	win_rate	franchID	G	W
130	ATL	1990	14555501.0	454859.406250	40.123457	ATL	162.0	65.0
131	BAL	1990	9680084.0	261623.891892	47.204969	BAL	161.0	76.0
132	BOS	1990	20558333.0	642447.906250	54.320988	BOS	162.0	88.0
133	CAL	1990	21720000.0	620571.428571	49.382716	ANA	162.0	80.0
134	CHA	1990	9491500.0	306177.419355	58.024691	CHW	162.0	94.0

In [12]:
```
teams['standardized_payroll'] = teams.groupby('yearID')['total_payroll'].transform(lambda x: (x - x.mean()) / x.std())
teams
```

Out[12]:

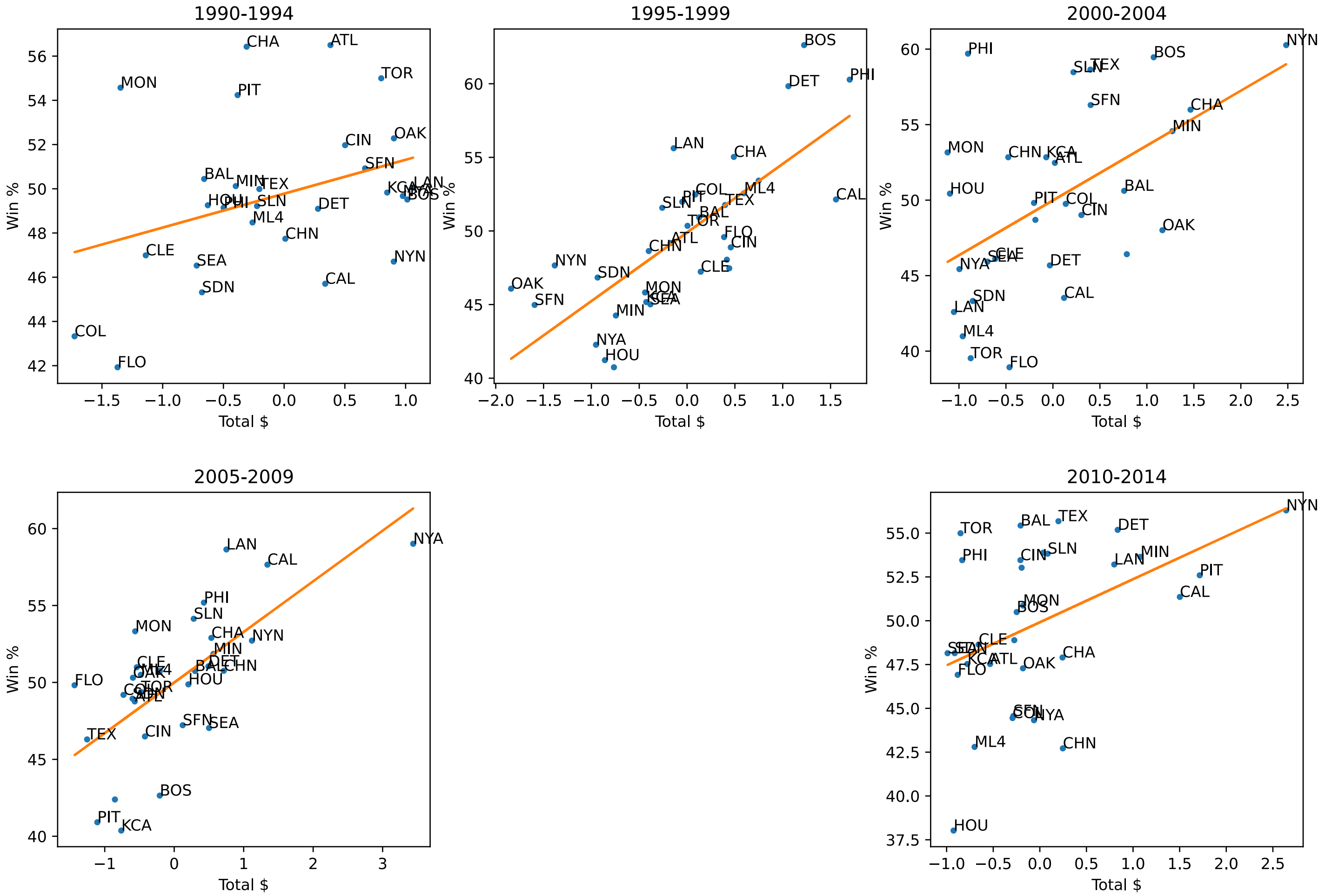
	teamID	yearID	total_payroll	mean_payroll	win_rate	franchID	G	W	standardized_payroll
130	ATL	1990	14555501.0	4.548594e+05	40.123457	ATL	162.0	65.0	-0.667275
131	BAL	1990	9680084.0	2.616239e+05	47.204969	BAL	161.0	76.0	-1.959861
132	BOS	1990	20558333.0	6.424479e+05	54.320988	BOS	162.0	88.0	0.924213
133	CAL	1990	21720000.0	6.205714e+05	49.382716	ANA	162.0	80.0	1.232198
134	CHA	1990	9491500.0	3.061774e+05	58.024691	CHW	162.0	94.0	-2.009859
...	...	...	...	...	...	...	...	...	...
855	SLN	2014	120693000.0	4.310464e+06	55.555556	STL	162.0	90.0	0.457126
856	TBA	2014	72689100.0	2.907564e+06	47.530864	TBD	162.0	77.0	-0.593171
857	TEX	2014	112255059.0	4.677294e+06	41.358025	TEX	162.0	67.0	0.272509
858	TOR	2014	109920100.0	4.396804e+06	51.234568	TOR	162.0	83.0	0.221422
859	WAS	2014	131983680.0	4.399456e+06	59.259259	WSN	162.0	96.0	0.704160

728 rows × 9 columns

Problem 6

Here I do the same thing as I did in problem 4 but the only difference is that I changed `total_payroll` to the `standarized_payroll` . The rest of the code is the same.

In [13]:
```python
section1 = teams[(teams['yearID'] >= 1990) & (teams['yearID'] <= 1994)]
section1 = section1.groupby('teamID', as_index=False)[["standardized_payroll", "win_rate"]].mean()

section2 = teams[(teams['yearID'] >= 1995) & (teams['yearID'] <= 1999)]
section2 = section2.groupby('teamID', as_index=False)[["standardized_payroll", "win_rate"]].mean()

section3 = teams[(teams['yearID'] >= 2000) & (teams['yearID'] <= 2004)]
section3 = section3.groupby('teamID', as_index=False)[["standardized_payroll", "win_rate"]].mean()

section4 = teams[(teams['yearID'] >= 2005) & (teams['yearID'] <= 2009)]
section4 = section4.groupby('teamID', as_index=False)[["standardized_payroll", "win_rate"]].mean()

section5 = teams[(teams['yearID'] >= 2010) & (teams['yearID'] <= 2014)]
section5 = section5.groupby('teamID', as_index=False)[["standardized_payroll", "win_rate"]].mean()

plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')

ax1 = plt.subplot(231)
ax2 = plt.subplot(232)
ax3 = plt.subplot(233)
ax4 = plt.subplot(234)
ax5 = plt.subplot(236)

plt.tight_layout(h_pad=5.0)

ax1.title.set_text('1990-1994')
ax2.title.set_text('1995-1999')
ax3.title.set_text('2000-2004')
ax4.title.set_text('2005-2009')
ax5.title.set_text('2010-2014')

ax1.set_xlabel('Total $')
ax2.set_xlabel('Total $')
ax3.set_xlabel('Total $')
ax4.set_xlabel('Total $')
ax5.set_xlabel('Total $')

ax1.set_ylabel('Win %')
ax2.set_ylabel('Win %')
ax3.set_ylabel('Win %')
ax4.set_ylabel('Win %')
ax5.set_ylabel('Win %')

ax1.plot(section1["standardized_payroll"], section1["win_rate"], '.')
ax2.plot(section2["standardized_payroll"], section2["win_rate"], '.')
ax3.plot(section3["standardized_payroll"], section3["win_rate"], '.')
ax4.plot(section4["standardized_payroll"], section4["win_rate"], '.')
ax5.plot(section5["standardized_payroll"], section5["win_rate"], '.')

for i, txt in enumerate(section1["teamID"]):
    ax1.annotate(txt, (section1["standardized_payroll"][i], section1["win_rate"][i]))
    ax2.annotate(txt, (section2["standardized_payroll"][i], section2["win_rate"][i]))
    ax3.annotate(txt, (section3["standardized_payroll"][i], section3["win_rate"][i]))
    ax4.annotate(txt, (section4["standardized_payroll"][i], section4["win_rate"][i]))
    ax5.annotate(txt, (section5["standardized_payroll"][i], section5["win_rate"][i]))


m, b = np.polyfit(section1["standardized_payroll"], section1["win_rate"],1)
ax1.plot(section1["standardized_payroll"], m * section1["standardized_payroll"] + b, '-')

m, b = np.polyfit(section2["standardized_payroll"], section2["win_rate"],1)
ax2.plot(section2["standardized_payroll"], m * section2["standardized_payroll"] + b, '-')

m, b = np.polyfit(section3["standardized_payroll"], section3["win_rate"],1)
ax3.plot(section3["standardized_payroll"], m * section3["standardized_payroll"] + b, '-')

m, b = np.polyfit(section4["standardized_payroll"], section4["win_rate"],1)
ax4.plot(section4["standardized_payroll"], m * section4["standardized_payroll"] + b, '-')

m, b = np.polyfit(section5["standardized_payroll"], section5["win_rate"],1)
ax5.plot(section5["standardized_payroll"], m * section5["standardized_payroll"] + b, '-')


plt.show()
```



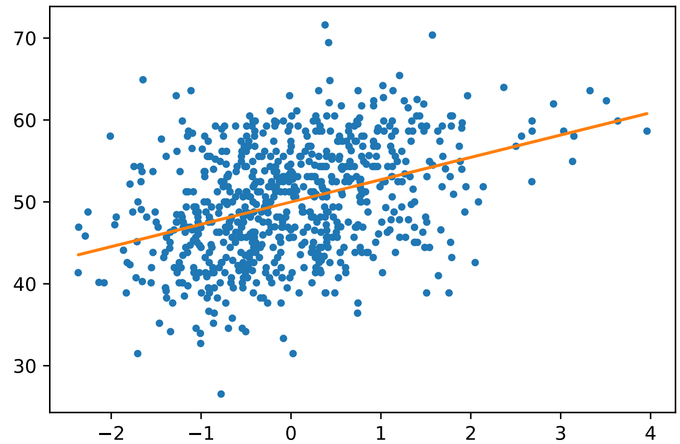
Question 3

These graphs represent the team standarized payrolls versus their win percentage across different time periods. By standarizing the data, we changed the actual range of the total payroll to the number of standard deviations away from the data mean. If we look at the graphs, they look the same as in problem 4 but the values in the x axis have changed to represent how far away from the mean they are. We can still see from our regression lines that it seems to be very consistent how the teams with the highest payrolls have the highest winrates. Also, we can see that NYA during the 2005-2009 period had the highest standard deviation. With this standarized variable, we can draw clearer conclusions and have a better idea of how differently each team performed.

Problem 7

For this part I used the `teams` dataframe with the added `standarized_payroll` column to plot it versus the `win_rate`. After that I used the `polyfit` numpy function to create a regression line to show the tendency of the graph. I also printed out the values of M and B that were given by the polifit to show that they are consistent with the values given in the project description.

In [14]:
```
plt.plot(teams["standardized_payroll"], teams["win_rate"], '.')
m, b = np.polyfit(teams["standardized_payroll"], teams["win_rate"],1)
plt.plot(teams["standardized_payroll"], m * teams["standardized_payroll"] + b, '-')
plt.show()
print(f'Value for b = {b} and value for m = {m}')
```




```
Value for b = 49.98855314843013 and value for m = 2.725103646155703
```

Problem 8

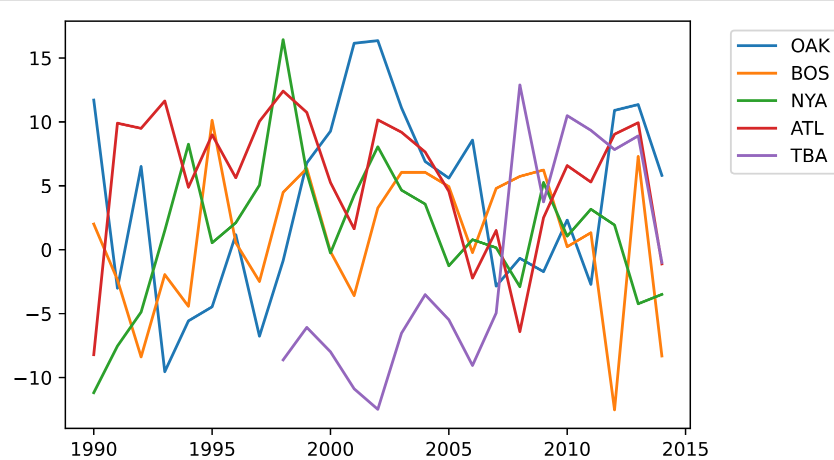
For this problem I first calculated the expected win percentage by using the values from B and M given by the project description. The formula is $expected = 50 + 2.5 * standarizedpayroll$. From this, we calculate the efficiency by subtracting the expected win percentage from the win percentage. After these calculations, I add the efficiency column to the `teams` dataframe. Now that I have the efficiency, I plotted the efficiency vs time for the teams Oakland, the New York Yankees, Boston, Atlanta and Tampa Bay.

In [15]:
```
teams['efficiency'] = teams['win_rate'] - ((teams['standardized_payroll'] * 2.5) + 50)
teams.head()
```

Out[15]:

	teamID	yearID	total_payroll	mean_payroll	win_rate	franchID	G	W	standardized_payroll	efficiency
130	ATL	1990	14555501.0	454859.406250	40.123457	ATL	162.0	65.0	-0.667275	-8.208354
131	BAL	1990	9680084.0	261623.891892	47.204969	BAL	161.0	76.0	-1.959861	2.104621
132	BOS	1990	20558333.0	642447.906250	54.320988	BOS	162.0	88.0	0.924213	2.010454
133	CAL	1990	21720000.0	620571.428571	49.382716	ANA	162.0	80.0	1.232198	-3.697779
134	CHA	1990	9491500.0	306177.419355	58.024691	CHW	162.0	94.0	-2.009859	13.049338

In [16]:
```
result = teams[teams["teamID"] == "OAK"]
plt.plot(result["yearID"], result["efficiency"], label="OAK")
result = teams[teams["teamID"] == "BOS"]
plt.plot(result["yearID"], result["efficiency"], label="BOS")
result = teams[teams["teamID"] == "NYA"]
plt.plot(result["yearID"], result["efficiency"], label="NYA")
result = teams[teams["teamID"] == "ATL"]
plt.plot(result["yearID"], result["efficiency"], label="ATL")
result = teams[teams["teamID"] == "TBA"]
plt.plot(result["yearID"], result["efficiency"], label="TBA")
plt.legend(bbox_to_anchor=(1.05, 1.0), loc='upper left')
plt.show()
```



Question 4

The plot above shows us the efficienty of Oakland, the New York Yankees, Boston, Atlanta and Tampa Bay throughout the years. From this plot we can see how efficient these teams were with their money. We can see that during the moneyball period, Oakland's efficiency is the highest out of all the other teams. They were able to use their money to the best of its ability. Comparing this to the plots in question 2 and 3, we can see that it tells a different story. In question 2 and 3 Oakland can be seen as a terrible team during the moneyball period but in reality they were extremely efficient with the money they had to pay their players as we see in the problem 8 plot.

Extra Credit

For the extra credit I went to the same website where we downloaded our data for the project but I navigated to the main page. From there I was able to go to the archive section and find the latest data for our dataset located here: [http://www.seanlahman.com/baseball-archive/statistics/ (http://www.seanlahman.com/baseball-archive/statistics/)](http://www.seanlahman.com/baseball-archive/statistics/) and here [https://github.com/chadwickbureau/baseballdatabank/tree/master/core (https://github.com/chadwickbureau/baseballdatabank/tree/master/core)](https://github.com/chadwickbureau/baseballdatabank/tree/master/core). The latest data for 2020 is only available in MS Access version, CSV, and in an R package. For this part, I decided to go with the CSV version and convert it to a SQLite database. Using `requests` library, I download the CSV files, I extract them and load them individually to a pandas dataframe. Once loaded into pandas, I can use the `to_sql` function to write it to our new database. For testing purposes and to prove that it has worked, I created a query to retrieve the Teams table. Here we can see the new 2020 data. This can also be done for all other tables used in the project and they will have all the latest data available.

In [17]:
```
import os
import requests, zipfile, io
r = requests.get("https://github.com/chadwickbureau/baseballdatabank/archive/master.zip")
z = zipfile.ZipFile(io.BytesIO(r.content))
z.extractall("./")


sqlite_file = 'lahman2020.sqlite'
conn = sqlite3.connect(sqlite_file)
path_to_data = "./baseballdatabank-master/core/"
for files in os.listdir(path_to_data):
    if files[-3:] == "csv":
        df = pandas.read_csv(f"{path_to_data}{files}")
        df.to_sql(files[:-4], conn, if_exists='append', index=False)

query = "SELECT * From Teams"

test = pandas.read_sql(query, conn)
test
```

Out[17]:

	yearID	lgID	teamID	franchID	divID	Rank	G	Ghome	W	L	...	DP	FP	name	park	attendance	BPF	PPF	teamIDBR	teamIDlahman45
0	1871	None	BS1	BNA	None	3	31	NaN	20	10	...	24	0.834	Boston Red Stockings	South End Grounds I	NaN	103	98	BOS	BS1
1	1871	None	CH1	CNA	None	2	28	NaN	19	9	...	16	0.829	Chicago White Stockings	Union Base-Ball Grounds	NaN	104	102	CHI	CH1
2	1871	None	CL1	CFC	None	8	29	NaN	10	19	...	15	0.818	Cleveland Forest Citys	National Association Grounds	NaN	96	100	CLE	CL1
3	1871	None	FW1	KEK	None	7	19	NaN	7	12	...	8	0.803	Fort Wayne Kekiongas	Hamilton Field	NaN	101	107	KEK	FW1
4	1871	None	NY2	NNA	None	5	33	NaN	16	17	...	14	0.840	New York Mutuals	Union Grounds (Brooklyn)	NaN	90	88	NYU	NY2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2950	2020	NL	SLN	STL	C	3	58	27.0	30	28	...	46	0.983	St. Louis Cardinals	Busch Stadium III	0.0	97	96	STL	SLN
2951	2020	AL	TBA	TBD	E	1	60	29.0	40	20	...	52	0.985	Tampa Bay Rays	Tropicana Field	0.0	96	95	TBR	TBA
2952	2020	AL	TEX	TEX	W	5	60	30.0	22	38	...	40	0.981	Texas Rangers	Globe Life Field	0.0	102	102	TEX	TEX
2953	2020	AL	TOR	TOR	E	3	60	26.0	32	28	...	47	0.982	Toronto Blue Jays	Sahlen Field	0.0	100	99	TOR	TOR
2954	2020	NL	WAS	WSN	E	4	60	33.0	26	34	...	48	0.981	Washington Nationals	Nationals Park	0.0	103	102	WSN	MON

2955 rows × 48 columns

In [ ]: